## Linear Solution to Scale and Rotation Invariant Object Matching

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## Problem





Target Mesh

# Challenges



#### Template Image



Target Images

## Challenges



#### Template Image



Target Images

## Some Related Methods

- Hough Transform and RANSAC
- Graph matching
  - Dynamic Programming
  - Max flow min cut [Ishikawa 2000, Roy 98]
  - Greedy schemes (ICM [Besag 86], Relaxation Labeling [Rosenfeld 76])
  - Back tracking with heuristics [Grimson 1988]
  - Graph Cuts [Boykov & Zabih 2001]
  - Belief Propagation [Pearl 88, Weiss 2001]
- Convex approximation [Berg 2005, Jiang 2007, etc.]

## The Outline of the Proposed Method

- A linear method to optimize the matching from template to target
- The linear approximation is simplified so that its size is largely decoupled from the number of target candidate features points
- Successive refinement for accurate matching

#### **The Optimization Problem**



#### In Compact Matrix Form



We will turn the terms in circles to linear approximations

## The L1 Norm Linearization

• It is well known that L1 norm is "linear"

$$\begin{array}{c} \min |x| & \longleftarrow & \min (y + z) \\ \text{Subject to } x = y - z \\ y, z \ge 0 \end{array}$$

• By using two auxiliary matrices Y and Z,  $| EMR - sEXT | \rightarrow 1'n_e (Y + Z) 1_2$ subject to Y - Z = EMR - sEXTY, Z >= 0

#### Linearize the Scale Term



 $sX = \sum_{l=1}^{n_s} s_l X_l \implies sEXT = \sum_{l=1}^{n_s} s_l EX_l T$ All sites select the same scale  $\sum_{l=1}^{n_s} s_l X_l 1_{n_t} = s1_{n_m}$ 

#### **Linearize Rotation Matrix**

$$\begin{array}{l} R'R = I & \longrightarrow \\ v & u \end{array} R = \begin{bmatrix} u & -v \\ v & u \end{bmatrix} \\ u \pm v = \pm 1, \quad |u| \leq 1, \ |v| \leq 1 \end{array}$$



## The Linear Optimization

LP: 
$$\min \varepsilon(X, s, u, v, Y, Z, X_1, \dots, X_{n_s}) = \operatorname{tr}(C'X) + \lambda \mathbf{1}'_{n_e}(Y + Z)\mathbf{1}_2$$
  
subject to  $Y - Z = EM \begin{bmatrix} u & -v \\ v & u \end{bmatrix} - \sum_{l=1}^{n_s} s_l EX_l T$   
 $Y, Z \ge 0, \quad u \pm v = \pm 1, \quad |u| \le 1, \quad |v| \le 1$   
 $X = \sum_{l=1}^{n_s} X_l, \quad X_l \ge 0, \forall l$   
 $\sum_{l=1}^{n_s} s_l X_l \mathbf{1}_{n_t} = s\mathbf{1}_{n_m}$   
 $X\mathbf{1}_{n_t} = \mathbf{1}_{n_m}, X \ge 0$   
Target point estimations

#### The Lower Convex Hull Property

 Cost surfaces can be replaced by their lower convex hulls without changing the LP solution



A cost "surface" for one point on the template

The lower convex hull

### **Removing Unnecessary Variables**

 Only the variables that correspond to the lower convex hull vertices need to be involved in the optimization



## Complexity of the LP



The size of the LP is largely decoupled from the number of target candidates

#### **Successive Refinement**





## Matching Objects in Real Images















#### **Result Videos**





## **Statistics**

	book	magazine	bear	butterfly	bee	fish
#frames	856	601	601	771	101	131
#model	151	409	235	124	206	130
#target	2143	1724	1683	1405	1029	7316
time	1.6s	11s	2.2s	1s	2s	0.9s
accuracy	99%	97%	88%	95%	79%	95%

## **Results Comparison**



#### Accuracy and Efficiency



## **Experiments on Ground Truth Data**



Error distributions for fish dataset

### **Experiments on Ground Truth Data**



Error distributions for random dot dataset

# Summary

- A linear method to solve scale and rotation invariant matching problems accurately and efficiently
  - The proposed method is flexible and can be used to match images using different features
  - It is useful for many applications including object detection, tracking and activity recognition
- Future Work
  - Multiple scale solution
  - More complex transformations
  - Articulated object matching